Self-Aware Wearable Systems in Epileptic Seizure Detection

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***Abstract*—Today, wearable systems are facing fundamental barriers in terms of battery lifetime and quality of their results. The main challenge in wearable systems is to increase the battery lifetime, while maintaining the machine-learning performance of the system. A recently proposed concept for overcoming this challenge is self-awareness, which increases system's knowledge of itself and the surrounding environment. This is precisely what health monitoring wearable systems require to adapt to different situations. To demonstrate the impact of introducing self-awareness in wearable technologies, we consider the epileptic seizure detection problem, as a case study. Epilepsy affects around 1% of the world's population, which can dramatically degrade the quality of life and represents a major public health issue. As a result, detection of epileptic seizures has become more important over the past decades. In this paper, we aim to introduce a new generation of self-aware wearable systems to decrease energy consumption and improve their seizures detection capabilities by introducing the notion of self-awareness in such systems. These techniques include switching to low-power mode to reduce the energy consumption and machine-learning model enhancement to improve detection quality. We incorporated our proposed techniques in the machine learning module, which detects epileptic seizures by monitoring the cardiac and respiratory systems. We evaluated the performance of our approach based on an epilepsy database of more than 141 hours, provided by the Lausanne University Hospital (CHUV). Our self-aware wearable system achieves 36% reduction in computational complexity and 10.51% improvement in detection performance.**

***Index Terms*—self-awareness, energy management, machine learning, epileptic seizure detection, classification.**

I. Introduction and related work

Self-awareness is perhaps the key to design intelligent systems that can continuously monitor their own performance, adapt to changes, and improve autonomously [1], [2]. The behaviour of a system is influenced significantly by its current state and the environment in which it is performing. As a result, to fulfill continuous high performance, having knowledge about self and environment is necessary for the system. Self-awareness can be applied to many different categories of systems equipped with control mechanisms and units, and usually has three major properties: Self-reflection, Self-prediction and Self-adaptation [3], [4]. According to these properties, each system should be aware of its architecture, execution environment, operational goals, and their corresponding dynamic changes during operation. It should also be able to predict the effect of dynamic changes and proactively adapt itself as the environment evolves in order to ensure that quality requirements are satisfied.

One category of systems in which self-awareness can play a significant role is bio-medical systems, where different conditions of a patient as well as the environment can significantly affect the output quality of the system. In particular, to perform more accurate remote health monitoring, the situation awareness and personalization parameters (such as age, gender, etc.) is considered in [5]. In addition, the authors consider the energy efficiency and dependability of the system via adjusting the priorities of the sensory data collection. In [6], the observation process, which transforms raw data into a high-quality description of the system about itself and its environment, is improved. This is done by measuring different parameters, such as, the confidence of the system and its relevance, as discussed on emotion recognition systems. Following the aforementioned examples of bio-medical systems, in this work we explore the benefits of introducing self-awareness in improving performance of wearable systems. In particular, we consider epileptic seizure detection as the target real-life case study for illustration of our approach.

Epilepsy is one of the most common chronic diseases affecting more than 50 million people worldwide [7]. Despite the recent advances in anti-epileptic drugs, one-third of the epileptic patients still suffer from this disorder. Moreover, epilepsy represents the second neurological cause of years of potential life lost, primarily due to seizure-triggered accidents and sudden unexpected death in epilepsy (SUDEP) [8]. To be able to notify family members, caregivers, and emergency units in case of a seizure for help, monitoring epileptic patients in real time is necessary. This can help reducing seizure-related injuries, status epilepticus, and SUDEP [9]. Although the gold standard in epilepsy monitoring is based on the video-electroencephalogram, due to its intrusive nature [10], [11], ECG monitoring has recently attracted a lot of attention.

There are several studies in monitoring ECG signals for epilepsy detection that mostly focus on selecting the best group of features to achieve highest detection performance. As an example, in [12], the authors achieve a sensitivity of 70% and a corresponding false-alarm rate of 2.11 per hour, using heart-rate variability features. In addition to heart-rate variability features, Lorenz plots are also used for epileptic seizure detection [13], [14]. In these studies, epileptic seizures of 13 out of 17 patients (76.47%) are detected, which still lacks the performance required for a reliable seizure detection system. To reach higher seizure detection performance, in [15], the authors combine heart-rate variability and Lorenz-plot features but they do not take into account the battery lifetime required for real-time monitoring of patients on a long-term basis. Despite all these efforts to have low energy consumption while achieving better detection performance, the state-of-the-art wearable technologies still suffer from insufficient battery lifetime and detection quality. Therefore, in this paper, we propose a new generation of self-aware wearable systems to cope with the stringout energy constraints of these bio-medical systems, while at the same time enhancing the detection quality they provide.

More precisely, in this work we target the design of a system for monitoring and detection of epileptic seizures based on the time series extracted from ECG signals. Hence, Our main contributions are as follows:

- Reducing the energy consumption of wearable systems by introducing the notion of self-awareness in such systems. Leveraging self-awareness such that the system can switch to a low-power mode when a simpler version of the system can fulfill the desired detection quality. We implemented this technique as a two-mode classifier in our seizure detection system using the Lausanne University Hospital (CHUV) database, which results in 36% reduction in detection complexity on the SmartCardia INYU wearable sensor [16].
- Improving system's detection quality by progressively refining the machine learning model using the self-awareness concept. The new incoming data, which we are confident about their labels, can improve the initial machine learning model and help to improve the detection quality. By applying this approach in our wearable seizure detection classifier, we achieve 10.51% improvement in terms of detection performance.

The rest of the paper is organized as follows. Section II contains the description of the general flow of wearable systems and our seizure detection system as a case study. In Section III, we focus on applying self-awareness in our system to perform energy management and detection quality enhancement. The experimental setup and results are provided in Section IV and V, respectively, where we evaluate the efficiency of our proposed solutions in terms of both classification performance and battery lifetime. Finally, in Section VI, we present the main conclusions of this work.

II. SEIZURE DETECTION SYSTEM

The overview of a typical wearable system for monitoring pathological health conditions is shown in Figure 1. In the training phase, there are often three main steps that wearable systems follow. There is a preprocessing phase at the beginning, in which different filters are applied to make the data ready for further steps. The features are then extracted from processed signal by taking different time-domain or frequency-domain characteristics of it, which are chosen according to the target system. In the final step, a machine learning algorithm, which is particularly selected and trained for the target problem, is used to extract the model and detect possible

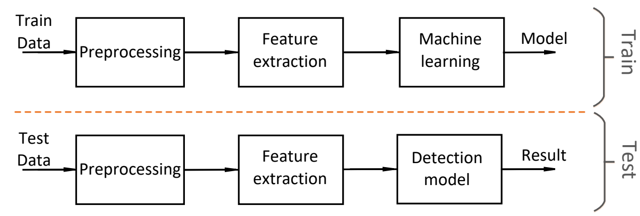

Figure 1: Overview of a typical wearable system for monitoring pathological health conditions

bio-medical abnormalities or pathologies. In the test phase, new data goes through the same preprocessing and feature extraction phases and after that the extracted model from the training phase is used to detect the results for the new data. Among the recent wearable systems, seizure prediction systems, based on the EEG signal in [17] follow the same structure as in Figure 1. To detect obstructive sleep apnea on wearable sensors, in [18], the exact same procedure is followed on the ECG signal. In [19], e-Glass, a wearable system based on four EEG electrodes for the detection of epileptic seizures is proposed, with the same flow depicted in Figure 1.

As a result, in this work, we revisit the design of epileptic seizure detection systems as main case study. However, conversely to previous systems, from a physiological viewpoint, we will use self-awareness to trade-off detection quality and power consumption and exploiting the fact that epileptic seizures have noticeable interaction with the autonomic nervous system (ANS) [20], leading to changes in the sympathetic and parasympathetic nervous activity [21]. These changes in ANS are reflected into changes in cardiac [21]–[23] and respiratory [24], [25] functions. The most common cardiac change associated with seizures is ictal tachycardia, often exceeding 100 bpm, while ictal bradycardia below 50 bpm is rare. Seizures can also alter the perception of respiration and fullness of breath (e.g., shortness of breath), respiratory rate and pattern (e.g., tachypnea, hypopnea, apnea), reflexes (e.g., coughing), quality (e.g., stridor), and secretions. Neurogenic pulmonary edema might also occur and could contribute to SUDEP [24], [25]. Analysis of these cardiac and respiratory characteristics is performed by monitoring of cardio-respiratory functions. In the following subsections, our epileptic seizure detection system is briefly described.

A. Pre-processing

In the first step, the ECG signal is segmented into windows of one-minute length with an overlap of 80% (48-second length). Then, a low-pass filter is applied for each window to remove frequencies above 60 Hz to reduce the noise, which is usually of a high frequency nature.

B. Features extraction

In this first phase of our wearable system design, the R-peak to R-peak interval (RRI) and ECG-Derived Respiration (EDR) time series are extracted from the ECG signal. The

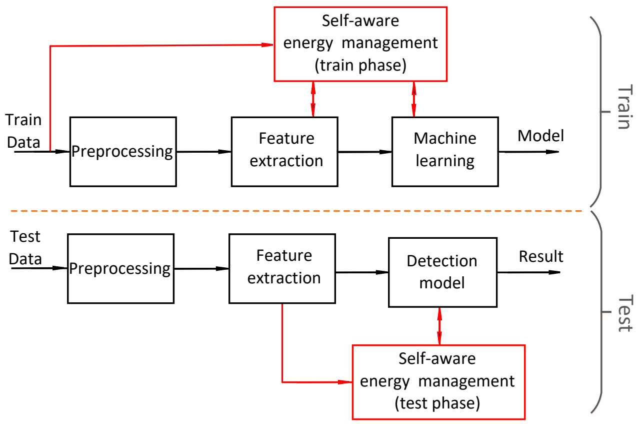

Figure 2: Overview of a typical wearable system for monitoring pathological health conditions after adding our self-aware energy-management units

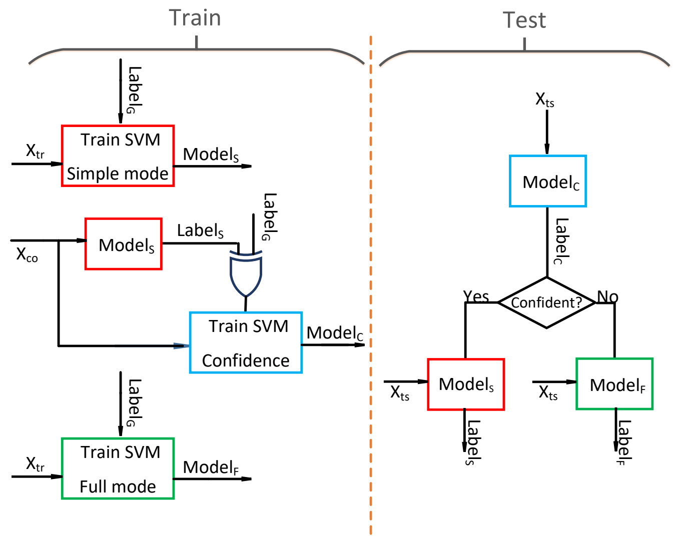

Figure 3: Training and test phase of our self-aware energy management

EDR time series is obtained by removing the baseline from the ECG signal, locating the R-peaks on pre-processed signal, and then calculating the area enclosed in the regions that are 100 msec beyond the R-peaks. The hearth-rate variability (which consists of time-domain and frequency-domain features of hearth-rate) and Lorenz plot of RRI (to capture the dynamic variation of the RR intervals) are calculated from the RRI time series. The linear predictive coefficients (LPC) that capture dependencies between the current sample of the EDR time series and the past few samples as well as the power spectral density are derived from the respiration time series as learning features.

C. *Machine learning*

At this stage, the extracted features are fed to a support vector machine (SVM) trainer with the radial-basis function (RBF) kernel to build a model for the classification of non-seizure (inter-ictal) and seizure (ictal) segments. Besides the high performance of SVM in terms of the accuracy of detecting seizures, SVM is also suitable to be implemented on resource-constrained embedded systems [26].

As mentioned in Section I, the main challenge in wearable monitoring systems is to provide high detection quality despite stringent resource constraints, as monitoring changes in signals of patients on a long-term basis is essential for providing real-time feedback in health monitors. This long-term monitoring is, however, not possible without ultra-low energy wearable systems. Introducing the concept of self-awareness in wearable technologies provides the opportunity of minimizing the energy consumed by the monitoring system equipped with the ability to know when it can operate in low-power mode (energy-saving mode). On the other hand, the self-awareness concept can improve the detection performance of the system by refining the detection model using the newly acquired data that is reliably classified by the system, as we explain in the next section.

III. Enhancing Self-Awareness in Wearables

Self-awareness techniques can be classified into two categories in the context of mobile health and wearable technologies. The first category is used for energy consumption reduction, in which the system can switch to low-power mode when the current input can be classified reliably by the simple classification model. The second category aims at increasing the accuracy of system by extracting new information from the newly acquired data. More detailed description of each category are provided in the following sections.

A. *Self-aware energy management*

To detect pathological health conditions using wearable system, often only a few prominent detection features are sufficient for confident classification [27]. However, according to the input data, these few prominent features cannot always separate normal and abnormal classes of data. In this work, we exploit this fact to improve the energy-efficiency of the system, while maintaining high detection performance thanks to a self-aware classification technique. In particular, to reduce the energy without sacrificing quality of detection, we propose a two-mode classifier. This novel classifier can work either in low-energy mode when a classifier with simple set of features can achieve the desired quality, or in complex mode in case that all features are required to meet the target detection quality of the running bio-medical application.

However, in order to take maximum benefit from this technique, the system has to be aware of the detection quality it can provide in each mode. To fulfill this ability, using the self-awareness concept, we introduce the notion of confidence that measures whether the result of the simple classifier is reliable or not. Therefore, the high-level overview of a wearable system after adding the self-aware energy-management unit is shown in Figure 2. This unit takes information from the feature

Algorithm 1 Self-aware classification - training phase

1: **function** TRAIN($X_{tr}, Label_G$)
2: Train: $Full\ SVM(X_{tr}, Label_G) \rightarrow Model_F$
3: Train: $Simple\ SVM(X_{tr}, Label_G) \rightarrow Model_S$
4: Predict: $Model_S(X_{tr}) \rightarrow Label_S$
5: Train: $Conf.\ SVM(X_{co}, Label_G \oplus Label_S) \rightarrow Model_C$
6: **return** Models $Model_C$, $Model_S$, $Model_F$
7: **end function**

Algorithm 2 Self-aware classification - test phase

1: **function** TEST($X_{ts}, Model_C, Model_S, Model_F$)
2: Predict: $Model_C(X_{ts}) \rightarrow Label_C$
3: **if** $Label_C = confident$ **then**
4: Predict: $Model_S(X_{ts}) \rightarrow Label_S$
5: **return** Label $Label_S$
6: **else**
7: Predict: $Model_F(X_{ts}) \rightarrow Label_F$
8: **return** Label $Label_F$
9: **end if**
10: **end function**

extraction unit and interacts with the machine learning unit. Then, Figure 3 shows the entire process of designing such self-aware learning algorithm for wearable systems.

The training phase of our classification procedure, which uses the notion of self-awareness and calculates the confidence model, is shown in Algorithm 1. In Lines 2–3, based on the training set X_{tr} and the corresponding ground-truth labels $Label_G$, two classifiers, a simple-mode SVM ($Simple\ SVM$) and a full-mode one ($Full\ SVM$) are trained. Then, we use the model from the simple classifier ($Model_S$) to predict the outputs corresponding to the training set X_{co} (Line 4). The ground-truth labels and the predicted ones are compared and the comparison result is used to train the confidence classifier ($Conf.\ SVM$) (Line 5). This classifier provides the system information about its current data by generating a model that shows whether the decision of the simple model is confident.

Then, the test phase of our classification procedure is shown in Algorithm 2. If the confidence model ($Model_C$) indicates that the classification based on the simple set of features (Line 2) is confident ($Label_C$) on the test data (X_{ts}), the simple classifier is used ($Label_S$) and the device is put in the low-power mode; otherwise, the full classifier, which is trained using all features in the training phase, is invoked ($Label_F$) (Lines 3–9).

B. Self-aware quality enhancement

The second challenge in wearable systems is quality improvement. The notion of self-awareness targets this challenge by introducing the ability of progressive learning in the system. This technique aims at enhancing the quality of wearables by improving the real-time pathology detection model using the new data that are acquired from the patient. Similar to the energy management techniques, the confidence notion is also considered here. The new data that are labeled as confident have a high chance to be classified correctly by the system. As

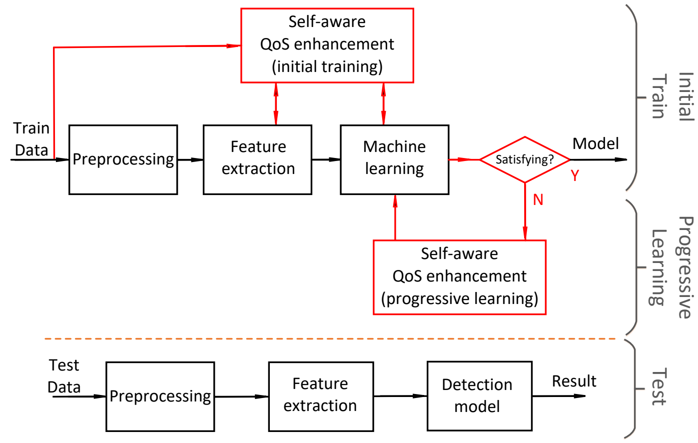

Figure 4: Overview of a typical wearable system for monitoring pathological health conditions after adding self-aware quality enhancement

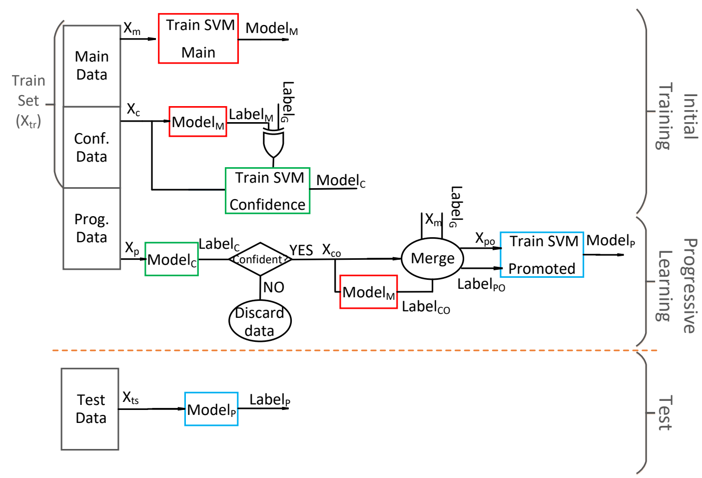

Figure 5: Quality enhancement technique by introducing the notion of self-awareness

a result, adding them and their corresponding decision (made by the classification model) to the training set can improve the model of the current classifier. The general overview of a wearable system after introducing the self-aware detection quality enhancement unit is shown in Figure 4. The initial training block takes information from the feature extraction unit and also interacts with the machine learning unit. The progressive learning unit interacts with the system iteratively and updates the current detection model continuously.

Then, as shown in Figure 5, to ensure generalization, in the offline training phase, there are two datasets. The first dataset is used to train the main classifier and the second dataset is used for training the confidence model by comparing result of the main classifier and the ground-truth (the labels are taken from the main classifier). After this phase, the confidence of the system on the new data that are acquired is measured

Algorithm 3 Quality enhancement - initial training and progressive learning

1: **function** TRAIN($X_{tr}, X_p, Label_G$)
2: Train: $Main\ SVM(X_m, Label_G) \rightarrow Model_M$
3: Predict: $Model_M(X_c) \rightarrow Label_M$
4: Train: $Conf.\ SVM(X_c, Label_G \oplus Label_M) \rightarrow Model_C$
5: Predict: $Model_C(X_p) \rightarrow Label_C$
6: **if** $Label_C = confident$ **then**
7: Predict: $Model_M(X_{co}) \rightarrow Label_{CO}$
8: $X_{po} = Merge(X_{co}, X_m)$
9: $Label_{PO} = Merge(Label_G, Label_{CO})$
10: **end if**
11: Train: $Promoted\ SVM(X_{po}, Label_{PO}) \rightarrow Model_P$
12: **return** $Model_P$
13: **end function**

based on this generated confidence model. Subsequently, the confident data (according to a certain defined threshold) is added to the training set to be used for the re-generation of the refined model.

The initial training phase as well as the progressive learning procedure of this model improvement are described in Algorithm 3. In Line 2, the main data (X_m) is trained by the main SVM ($Model_M$). The confidence data (X_c) is then classified by this model ($Label_M$) and the XOR of this result and the ground-truth labels ($Label_G$) are used to train the confidence model ($Model_C$) (Line 3–4). The progress data (X_p) is then classified by the confidence model ($Label_C$). If the data is confident (X_{co}), we add the data to the improved dataset (X_{po}) and add the result of $Model_M$ on this data ($Label_{CO}$) to the improved labels ($Label_{PO}$) (Line 5–10). In the last step, we train the improved SVM with X_{po} and $Label_{PO}$ ($Model_P$) and return the improved model. The testing phase consists of classifying the test data (X_{ts}) with the improved model.

In the presence of more data, the quality enhancement scheme can be broken into an iterative model refinement procedure in which the quality increases in each iteration. This is called mini-batch, which is an algorithm that splits the training dataset into small batches that are used, in each iteration, to update the model. In that case, considering the power of this model improvement technique and its complexity, a time period is chosen to collect the new data. In each period, the incoming data are collected and used for progressive learning and a new model in generated. This procedure continues until the desired quality is achieved.

IV. Experimental setup

As described in Section II, we consider our wearable epileptic seizure detection system as a real-life case study to demonstrate the effectiveness of our proposed self-awareness system. Therefore, in the following, we show the impact of self-awareness in both energy consumption reduction and QoS enhancement.

A. Datasets

The proposed self-aware wearable system design approach was evaluated with the CHUV dataset, which includes single-lead ECG data for 7 patients. The overall dataset includes more than 141 hours of recordings with 34 seizures. The data was acquired at a sampling rate of 256 Hz, where every sample is represented by 16 bits. Further details are provided in Table I.

Table I: Details of patient's dataset.

Patient	No. of hours	No. of seizures
Patient 1	18.12	8
Patient 2	32.59	6
Patient 3	5.07	6
Patient 4	17.26	5
Patient 5	17.21	3
Patient 6	32.77	3
Patient 7	18.00	3
Total	**141.02**	**34**

B. Performance metrics

To evaluate the performance of our proposed system, we apply the leave-one-out strategy for testing, where one recording is left out for testing and the rest of the recordings are used for training. This process is repeated to test all recordings. To measure the performance of the classification scheme, we consider four important definitions:

- False positive (FP): The sample is classified as ictal wrongly.
- True negative (TN): The sample is classified as inter-ictal correctly.
- True positive (TP): The sample is classified as ictal correctly.
- False negative (FN): The sample is classified as inter-ictal wrongly.

Three metrics are extracted from these definitions: specificity ($Spec$), which shows the percentage of inter-ictal samples that are labeled wrongly, sensitivity (Sen), which represents the percentage of ictal samples that are labeled correctly, and the geometric mean ($gmean$), which reflects both specificity and sensitivity [28]. The desirable case is having high $gmean$, which is equivlent to high $Spec$ and Sen. These metrics are defined as follows:

$$Spec = \frac{TN}{FP + TN}, \tag{1}$$

$$Sen = \frac{TP}{TP + FN}, \tag{2}$$

$$gmean = \sqrt{Spec \cdot Sen}. \tag{3}$$

C. Implementation platform

To estimate the battery lifetime of the proposed wearable system, the SmartCardia INYU wearable sensor [16] is used as target hardware platform as an example of a typical wearable system. Using this device the single-lead ECG recording is acquired with an operating frequency between 250 Hz and 1 kHz. The ECG signal acquisition is performed using silver-chloride electrodes by impedance pneumography [29]. The processor for data analysis and classification is an ARM

Table II: Comparison between the energy-efficiency of seizure detection system with our self-aware energy management (SAEM) and without any energy management (WOEM).

	WOEM			SAEM		
Metric	Specificity	Sensitivity	Gmean	Specificity	Sensitivity	Gmean
Average	90.69%	86.83%	88.74%	89.86%	88.96%	89.41%

Table III: Comparison between the execution time of the wearable seizure detection system including our self-aware energy management (SAEM) and without any energy management (WOEM)

Method	Execution part	Execution time (ms)
WOEM	Complex classifier	840.00
SAEM	Simple classifier	30.00
	Complex classifier	840.00
	Self-aware classifier	537.71

Cortex-M3 chipset (STM32L151RDT6) [30], which is a low-power 32-bit microcontroller with 48 kB RAM and 384 kB flash storage and the maximum frequency of 32 MHz. The processor has several power modes, including an active and a sleep mode, with the possibility of dynamically switching between different modes. The INYU device is powered by a 710 mAh battery.

V. Experimental results

In this section, we evaluate the QoS enhancement and energy reduction techniques considering the CHUV dataset to analyze the advantages of introducing the self-awareness notion in the epileptic seizure detection system, as a real-life case study.

A. Energy consumption reduction results

To show the effectiveness of our energy reduction technique in this case study, we compare the system with and without using our self-aware energy management technique. The reduced set of features for simple mode classification in this case study are: meanNN, SDNN, RMSSD, total power, and NN50 from HRV features [12] in addition to the Lorenz-plot features [13]. First, we investigate if this self-aware technique has any negative impact in terms of classification and seizure detection performance. The results of accuracy are shown in Table II and indicate that, as we are using the full classifier for all data that the simple classifier is not confident about, the performance of the proposed system without energy management (WOEM) is not degraded by our technique (SAEM).

Then, in order to evaluate the effectiveness of this approach in terms of complexity, the execution time of classification process for WOEM and SAEM systems are compared in Table III. The processing time of our proposed approach with energy management (SAEM) is calculated based on Equation (4), where the total execution time of our proposed technique is derived as follows:

$$T_{execution} = T_C + P \cdot T_S + (1 - P) \cdot T_F, \tag{4}$$

Table IV: Comparison between the classification quality with and without our proposed self-aware system for model refinement

SVM Model	Confident data portion %	Specificity %	Sensitivity %	Gmean %
Original	–	94.31	69.57	70.03
Promoted	77.78	97.66	80.43	80.54

where $T_{execution}$ is the total execution time of our self-aware classification technique, P is the probability of invoking the simple mode (obtained experimentally), and T_C, T_S, and T_F are the execution times of the confidence calculation, simple classifier, and complex classifier, respectively. According to the Table III, T_S and T_F are 30.00 ms and 840.00 ms, respectively, and T_C is negligible. The probability of invoking the simple classifier (P) is 37.32% for the CHUV database, which is measured experimentally.

Applying our self-aware energy management technique, the complexity of our system is reduced by 36%, as the execution time of the classifier is reduced from 840.00 ms in WOEM method to 537.71 ms in SAEM method. This demonstrates the effectiveness of our proposed self-aware energy management technique. Moreover, the reduction in complexity, which is achieved by applying our technique, does not come at the cost of QoS degradation.

B. QoS enhancement results

To evaluate the impact of QoS enhancement using our proposed self-awareness notion, the results of seizure detection using the main model and improved model (as discussed in Section III) are compared in Table IV. The values are average over all patients results in leave-one-out method. As shown in this table, using this technique improves the absolute geometrical mean by 10.51%, which is equal to 15% relative improvement of geometric mean when compared to the original result. We also observe that while this approach improves both sensitivity and specificity, the latter changes more significantly, which indicates that the true positive is increased significantly due to our proposed model refinement. In addition, by using this technique, we can start with an initial model and progressively refine its results by adding informative data. Indeed, when the new data are more probable to contain new information, this technique leads to better results.

VI. Conclusion

In this paper, we have presented how to introduce the notion of self-awareness into wearable systems as a novel approach to reduce their energy consumption, while guaranteeing the QoS of the system. We considered an epileptic seizure detection system as our real-life case study and validated our approach based on the CHUV epilepsy database. Overall, the notion of self-awareness reduced the detection complexity of the wearable system using the self-aware classifier by 36% and also improved the detection performance using the self-aware refinement of the model by 10.51%. Therefore, these experimental results demonstrate that self-awareness can have significant benefits for both QoS and lifetime of wearable systems.

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